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Citation for published version:

Bosche, F & Haas, CT 2008, 'Automated retrieval of 3D CAD model objects in construction range images', *Automation in Construction*, vol. 17, no. 4, pp. 499-512. <https://doi.org/10.1016/j.autcon.2007.09.001>

Digital Object Identifier (DOI):

[10.1016/j.autcon.2007.09.001](https://doi.org/10.1016/j.autcon.2007.09.001)

Link:

[Link to publication record in Heriot-Watt Research Portal](#)

Document Version:

Peer reviewed version

Published In:

Automation in Construction

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Automated Retrieval of 3D CAD Model Objects in Construction Range Images

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Abstract

Automated and robust retrieval of three-dimensional (3D) Computer-Aided Design (CAD) objects from laser scanned data would have many potentially valuable applications in construction engineering and management. For example, it would enable automated progress assessment for effortless productivity tracking, automated 3D image database searching for forensic and legal analysis, and real-time local modeling for automated equipment control and safety. After reviewing and analyzing previous research in the field of automated object recognition, this paper presents a new approach for robust automated recognition/retrieval of 3D CAD objects in range point clouds in the Architectural/Engineering/Construction & Facility Management (AEC-FM) context. This approach is validated in laboratory experiments. A first experiment demonstrates that this new approach can efficiently and robustly automatically retrieve 3D CAD model objects in construction laser scanned data. A second experiment demonstrates how this approach can be used for efficiently assessing construction progress. The results presented here are preliminary but conclusive for proof of concept. More extensive field experiments in this and other application areas will follow to characterize performance trade-offs in practice.

Key words: Laser scanner, Range point cloud, Computer aided design, Data referencing, Automated object recognition.

PACS:

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1 Introduction

The Architectural/Engineering/Construction - Facility Management (AEC-FM) industry constantly needs to assess project performance with as much precision as possible and as fast as possible. Performance is tracked using metrics that meaningfully and efficiently estimate it. For instance, construction progress and productivity tracking requires assessing progress in terms of quantities and elements put in place, tests conducted, etc. Construction quality assessment requires, among other aspects, assessing the three-dimensional (3D) similarity between as-built and as-planned 3D objects. Similarly, construction dispute resolution and forensic analysis may in the future require exhaustive searches of range point cloud databases to acquire incontrovertible evidence of facts on the ground. In all these examples quantities and structural elements can be described in design documents and tracked as 3D shapes. Tracking quantities, elements, and quality automatically with the aid of automated recognition/retrieval of 3D Computer-Aided Design (CAD) objects from construction range point clouds would thus be beneficial and is possible with the method described in this paper. For brevity, the authors focus primarily in this paper on the application to construction progress tracking.

Traditional practice for construction progress assessment relies on intensive manual data collection and processing. This is labor intensive, expensive, and generally results in partial and sometimes erroneous information. As a result, it is difficult to make appropriate and timely management decisions ([1]; [2]; [3]).

The recent and rapid development of laser scanners, also referred to as LAser Detection And Ranging (LADAR), allows precise and comprehensive acquisition of range point clouds. Laser range point clouds are often referred to as *range images* or $2\frac{1}{2}D$ data because they contain 3D information about visible surfaces only. In the specific context of construction progress assessment, laser scanners can be used to acquire range point clouds from an asset in construction at any time. Acquired range point clouds can be analyzed to identify the presence of 3D project objects, so that the quantity of work that has been performed up to that specific time can be estimated. The advantage of using laser scanning data for assessing construction progress is that it directly identifies in-place quantities. It is thus potentially more robust than and at least complementary to other approaches that indirectly calculate work progress — e.g. by recording in real-time the location of construction resources for inferring production quantities ([3]; [4]). However, industry managers could benefit from laser scanning technologies for effortless construction progress tracking only if they can be used to obtain reliable and high-value information, rapidly and, if possible, automatically [5].

41 A new approach is presented in this paper that allows robust automated re-
 42 trieval of 3D CAD objects from range images. Sections 2 and 3 review exist-
 43 ing approaches for automated object recognition in sensed data, and analyze
 44 their applicability and expected efficiency and robustness in the investigated
 45 context. This analysis leads to the formulation of a new approach described
 46 in Section 4. Section 5 presents two laboratory experiments, conducted in
 47 the Centre for Pavement And Transportation Technologies (CPATT) at the
 48 University of Waterloo, that validate this new approach and demonstrate its
 49 applicability to automated construction progress tracking. Section 6 then dis-
 50 cusses the impact of measurement uncertainties on the proposed approach and
 51 suggests methods to take them into account. Finally, Section 7 discusses the
 52 estimations of the different parameters used in the proposed approach and
 53 how these could be automated.

54 2 Automated Recognition of 3D Objects in Range Images

55 2.1 Common Approaches to the Object Recognition Problem

56 The automated recognition of objects in sensed data, also referred to as *object*
 57 *recognition* is not a new problem and previous research in this field has been
 58 extensive, especially for application in robotics. In [6], Arman & Aggarwal
 59 propose a definition of the *object recognition problem* as “*locating a desired*
 60 *object in a scene and determining its exact location and orientation*”. In this
 61 definition, the combination of the location and orientation of an object is
 62 also generally referred to as its *pose*. Systems performing object recognition
 63 must have some *a priori* knowledge of the search object(s) (e.g. shape, color,
 64 temperature). This *a priori* knowledge is generally contained in an object
 65 *model*. As a result, such systems are generally referred to as *model-based object*
 66 *recognition systems* and they generally follow the following process:

- 67 (1) A data representation is chosen to meaningfully describe the object model,
- 68 (2) Features are extracted from the object model described using the chosen
 69 data representation,
- 70 (3) Features are extracted from the sensed data described using the same
 71 data representation,
- 72 (4) Object features are matched to sensed data features in order to infer the
 73 recognition of the object,
- 74 (5) The poses of recognized objects are estimated.

75 The choice of the data *representation* determines the recognition strategy and
 76 thus has a significant impact on the efficiency and robustness of the recognition
 77 system. An adequate representation is: unambiguous, unique, not sensitive,

78 and convenient to use [6]. A review of most common strategies for object
79 recognition can be found in [6] and some examples of systems for automated
80 recognition of 3D objects in range images can be found in [7], [8] and [9].

81 The main challenge faced by typical model-based object recognition systems
82 is that they are based on the extraction of features from both the search
83 objects' models and the sensed data. These systems can be referred to as
84 *feature-based* model-based object recognition systems. The level of difficulty
85 in the extraction of features increases with the "complexity" of the search
86 context, and this "complexity" is related to the following factors:

87 **Unknown pose of each object.** Object recognition systems generally as-
88 sume that the pose of each object is *a priori* unknown. This assumption is
89 genuine in most general search cases when the only *a priori* knowledge is
90 the set of search object models.

91 **Unknown relative pose of search objects** . Similarly, object recognition
92 systems generally assume that the relative pose of two search objects is *a*
93 *priori* unknown. This assumption is also genuine in most general search
94 cases.

95 **Number of search objects.** Object recognition systems generally search for
96 objects one at a time in the scanned data. As a result, their computational
97 complexity is proportional to the total number of search objects.

98 **Occluded and cluttered scenes.** Most object recognition systems genuinely
99 assume that scanned scenes may include data about any object, searched
100 or not searched. This however makes efficient and robust automated feature
101 extraction very difficult.

102 2.1.1 *Spin-Image Approach*

103 In [8], Johnson & Hebert present another *model-based* approach that is based
104 on 2D data representations called *spin images*. This approach is interesting
105 because it is not *feature-based* as spin-images of the entire range data are
106 directly compared to the spin-images of the search objects' models. In this
107 approach, recognition is achieved as follows:

- 108 (1) All search objects are represented as polygonal surface meshes,
- 109 (2) A spin image is calculated for each vertex of the mesh representation of
110 each object,
- 111 (3) The scanned data is represented as a polygonal surface mesh,
- 112 (4) Random vertices are identified in the sensed data mesh and spin images
113 are calculated for each of them,
- 114 (5) Each spin image obtained from the sensed data is matched with all spin
115 images of the search objects,
- 116 (6) For each object, if several spin-image correspondences are found, this

117 object is considered recognized and its pose is estimated.

118 The main advantage of this approach is that it is not feature-based and thus
119 does not suffer from the limitations of feature extraction algorithms. Addi-
120 tionally, this approach appears fairly efficient with occluded and cluttered
121 scenes (in the experiments, objects up to 68% occluded were systematically
122 retrieved). Nonetheless, this method also presents some limitations:

- 123 ○ The scanned scene is approximated with a polygon tessellation, which re-
124 sults in a loss of information originally contained in the range image.
- 125 ○ Not all vertices in the scanned data mesh are investigated (20 to 50%),
126 meaning that small or very occluded objects are likely to be missed. This
127 could be avoided by investigating all vertices in the scanned data mesh, but
128 would result in a computational complexity proportional to the number of
129 vertices in the scanned scene mesh, which can be very high.
- 130 ○ Computational complexity is proportional to the number of objects and the
131 number of spin images for each object. In [8], Johnson & Hebert nonetheless
132 show that, for each object, Principal Component Analysis can be used to
133 at least reduce the search domain constituted by all its spin images.
- 134 ○ The pose of objects presenting symmetries cannot be ensured since the spin
135 image of a symmetrical object in one pose is exactly the same as the one in
136 its symmetrical pose.
- 137 ○ Although this method is reasonably robust with object occlusions, it could
138 be argued that it would be interesting to be able to retrieve objects more
139 than 70% occluded. Recognition of more highly occluded objects could prob-
140 ably be achieved here if all vertices in the scanned data were investigated,
141 but, as explained above, this would result in higher computational complex-
142 ity.
- 143 ○ Finally, this approach recognizes objects by matching 2D object character-
144 istics (spin images). This implies that some information contained in the
145 $2\frac{1}{2}$ D range data is not only lost while performing the data tessellation, but
146 also while calculating each spin image.

147 2.2 Application to the Investigated Problem

148 The investigated problem of automatically retrieving all construction project
149 objects present in a construction site range image has the following character-
150 istics:

- 151 ○ The number of objects that should be searched in the scan is the number of
152 3D construction objects constituting the project model, which can be very
153 large. Additionally, the shape of search objects can be very complex.
- 154 ○ Construction site scenes are generally very occluded and cluttered. Also,

many project elements might be scanned in partial construction status (e.g. partially built walls and columns).

As a result, if feature-based object recognition approaches were to be used in this specific context, they would generally be too computationally complex and would result in limited recognition results as construction scenes are too complex for efficient and robust 3D feature extraction. This feature extraction complexity is also increased by the fact that it is not possible to recognize all the features of a given model in one range point cloud due to occlusions and the fact that range information is only $2\frac{1}{2}D$. Previous works in civil engineering investigating the use of feature-based object recognition approaches to this problem acknowledge these limitations ([10], [11],[12]).

Similarly, if the spin-image approach was used, it would generally be too computationally complex due to the number of search objects, the number of spin images for each object, and the number of scanned points. Also, it could suffer from the highly cluttered and occluded characteristic of construction scenes. Nonetheless, the spin-image approach would likely be more robust than feature-based object recognition approaches. The spin-image approach is thus further investigated and feature-based approaches are discarded for the remaining of this analysis.

3 The Context: New AEC-FM Technologies

3.1 Project 3D CAD Models

In recent decades, the AEC-FM industry has been experiencing a rapid increase in the use of project 3D/4D CAD models. Project 3D CAD engines allow for the development of exact and comprehensive project designs in the form of 3D models. Project 4D CAD models enhance project 3D CAD models with schedule information. Project 3D/4D models undeniably increase design quality, management and communication among stakeholders, and decrease the number and impact of changes occurring during the project life cycle [13]. Additionally, they are now used as the central components of more complex AEC-FM management models such as Building Information Models (BIM).

Project 3D/4D CAD models do not constitute a basic library, but a spatially organized library of the project 3D objects. The relative pose of each pair of 3D project objects is thus expected to be the same in the 3D CAD model as in reality once they are built. Consequently, by using project 3D CAD models in 3D object recognition systems, the recognition of one object would provide *a priori* information on where to search for all the other objects. Or,

191 from another perspective, the entire project 3D CAD model could be searched
192 simultaneously.

193 Project 3D CAD models present another interesting advantage, regarding oc-
194 clusions. From a given project 3D view point, all occlusions to a project 3D
195 object due to other project 3D objects are expected to occur similarly in
196 reality and in the project 3D CAD model. Such information, if efficiently in-
197 corporated in 3D object recognition systems, could significantly improve their
198 robustness, especially when dealing with potentially very occluded scenes such
199 as construction sites.

200 3.2 (Geo-) Referencing

201 Along with 3D CAD engines, global positioning technologies (i.e. GPS for
202 location and digital compasses for orientation) are being used more in the
203 AEC-FM industry since their accuracy and precision have become acceptable.
204 Regarding location estimation, while Differential GPS (DGPS) can achieve
205 sub-feet accuracy, Relative Kinematic Positioning (RKP) GPS technology can
206 improve location estimation accuracy up to a couple of inches. Further, GPS
207 technologies remain a major area of research and it is not unrealistic to imagine
208 sub-inch accuracy systems in the near future. Similar conclusions can be made
209 for orientation estimation systems such as digital compasses that typically
210 achieve accuracies of half a degree.

211 Both field data and 3D CAD models can be geo-referenced. Therefore, field
212 data can be typically registered into the coordinate frame of the model. In
213 the AEC-FM industry, global positioning technologies are thus already used
214 to enable management to track position of any type of important resource in
215 real-time on project sites for applications as diverse as productivity tracking,
216 lay-down yard management or safety.

217 In the problem investigated here, using (geo-) referencing technologies would
218 simplify the search of the project 3D CAD model in the scanned data as the
219 position of each search object in the scanned data would be *a priori* known (at
220 least estimated). The authors acknowledge the limited accuracies of current
221 (geo-) referencing technologies. Nonetheless, these technologies can be used to
222 at least provide good pose estimations, and Section 6 discusses how, in the
223 investigated problem, the pose of 3D CAD model in the scanned data could
224 be optimized once a good estimation is obtained.

226 The technologies above — that are already being used on construction projects
 227 but in other applications — could be leveraged in the investigated problem.
 228 Used with the spin-image approach, it seems that its major limitation — its
 229 computational complexity due to the number of search objects and the number
 230 of vertices in the scanned scene mesh — could be significantly reduced. Indeed,
 231 the project model could be searched all at once, and for each scanned scene
 232 mesh vertex, the project model mesh vertex for which the spin-image matching
 233 should provide the best result can be known *a priori*. Finally, thanks to the
 234 3D referencing, the limitation of this method with symmetrical objects is also
 235 overcome.

236 However, it must be noted that the spin-image approach provides results re-
 237 garding the overall recognition of each search object, but it is not suited to
 238 provide detailed recognition results of parts of the search object. The recog-
 239 nition of each individual project object is important in the investigated prob-
 240 lem. Therefore, each object must thus be searched individually, not the entire
 241 project 3D model simultaneously, and the complexity of the spin-image ap-
 242 proach remains proportional to the number of search objects. Additionally,
 243 this method is based on the approximation of the sensed data by polygon tes-
 244 sellation, which results in a loss of information contained in the original data.
 245 Finally, the data matching is based on a 2D data representation (spin-image).
 246 The representation of the $2\frac{1}{2}$ D range data using spin-images thus further re-
 247 duces the amount of information available for the matching process. As a
 248 result, the spin image approach cannot achieve optimum object recognition as
 249 it considers only part of the information contained in the acquired range data.

250 Despite these limitations, the authors acknowledge the apparent robustness of
 251 the spin-image -based 3D object recognition approach. A new model-based 3D
 252 object recognition approach is nonetheless presented here. This approach uses
 253 the sensed data (scanned point cloud) in its raw format, it is not feature-based,
 254 and its complexity is not proportional to the number of search objects as the
 255 entire project model is searched simultaneously. As a result, this approach
 256 is expected to be both efficient and robust for the automated recognition of
 257 project 3D CAD objects in construction range images.

258 4 New Approach

259 The proposed new approach is based on the idea that, since the performance
 260 of any approach for automated recognition of 3D object in range images is
 261 constrained by the sensed data, the best recognition approach can only be

262 obtained if the sensed data is used in its natural representation, here the
 263 range point cloud. As a result, the authors propose an approach that uses
 264 the range point cloud as the common 3D object data representation. This
 265 implies that the project 3D CAD model must be represented as an equiva-
 266 lent range point cloud. To do this, (geo)-referencing information is used to
 267 reference the project 3D CAD model in the laser scanner’s spherical coordi-
 268 nate frame. Then, for each as-built range point, a corresponding range point
 269 is calculated using the project 3D CAD model as a virtual world. This vir-
 270 tual world can also be referred to as the *expected world* or *as-planned world*
 271 and the point cloud resulting from the virtual scan conducted in this virtual
 272 world can be referred to as the *as-planned point cloud* (by comparison to the
 273 real *as-built point cloud*). As-built point features include at least three spatial
 274 coordinates, that are sometimes enhanced with reflectivity and color infor-
 275 mation. Similarly, as-planned point features include three spatial coordinates
 276 as well as any additional information that can be extracted from the project
 277 3D CAD model when calculating the as-planned point cloud. These features
 278 may include object color and object reflectivity. But more importantly, one
 279 additional as-planned point feature that can systematically be extracted from
 280 the project 3D CAD model is the “*ID/name*” of the object from which each
 281 as-planned range point is obtained.

282 The challenge of this approach consequently lies on the calculation of the
 283 *as-planned point cloud*. A method for this calculation is presented in Section
 284 4.2. Then, Section 4.3 presents the two metrics that are used for automat-
 285 ically comparing as-built and as-planned point clouds in order to infer the
 286 retrieval/recognition of all project 3D model objects.

287 4.1 Project 3D CAD Model Format

288 Full access to the information contained in the project 3D CAD model is
 289 necessary in order to practically calculate the as-planned point cloud. However,
 290 project 3D/4D models generally present the project 3D as-planned data in
 291 a proprietary 3D CAD engine format (e.g. DXF, DWG, DGN, etc.). Since
 292 these proprietary formats are protected, the as-planned point cloud calculation
 293 requires the project 3D CAD model be converted into an open-source 3D
 294 format. This open-source format must be chosen so that the conversion results
 295 in as little loss of 3D information as possible.

296 In [14] the authors identify one good candidate format that meets this in-
 297 formation preservation requirement : the STereoLithography (STL) format.
 298 Detailed information about this format that approximates volume envelopes
 299 by tessellations of triangles can be found in [15]. It might be argued that, if
 300 access to proprietary formats is granted, this conversion would not be nec-

301 essary anymore. However, it will be shown in the next section that polygon
 302 tessellation-based formats such as the STL format present an additional advan-
 303 tage over native CAD engine formats with respect to the proposed approach.

304 4.2 Calculation of the As-planned Point Cloud

305 The as-planned range point cloud can now be calculated as follows:

- 306 (1) Using the (geo-) reference information, the STL-formatted project 3D
 307 CAD model is referenced in the laser scanner’s spherical frame. In this
 308 coordinate frame, the coordinates of each STL triangle composing the en-
 309 velop of each object of the project model can be expressed using spherical
 310 coordinates (instead of natural Cartesian coordinates).
- 311 (2) For each as-built range point, the corresponding as-planned range point
 312 is assigned the same pan and tilt angles. Then, its range is calculated by
 313 finding the closest STL triangle intersected by the “ray” traced in the
 314 direction defined by these pan and angle angles.

315 The identification of the closest STL triangle intersected by a ray is a con-
 316 strained version of the calculation of the projection of a point on a plane in
 317 a given direction. This problem is fairly straight-forward so that the solution
 318 won’t be detailed here. Instead, the authors want to emphasize the fact that
 319 the combination of the project 3D CAD model being referenced in the laser
 320 scanner’s spherical frame and the project 3D CAD model being converted into
 321 the STL format presents an opportunity for significant reduction in the compu-
 322 tational complexity of the identification of the closest STL triangle intersected
 323 by a ray and thus of the calculation of each as-planned range point. Indeed,
 324 in this spherical frame, all the vertices of all the STL triangles are expressed
 325 with spherical coordinates: pan, tilt and range. As a result, the bounding pan
 326 and tilt values of each STL triangle can be identified. Then, as illustrated in
 327 Figure 1, it can be noted that the intersection of a ray defined by the two
 328 angles pan_0 and $tilt_0$ can only intersect a STL triangle whose bounding pan
 329 and tilt angles actually surround the pan_0 and $tilt_0$ values. This implies that
 330 the closest intersected STL triangle can be rapidly identified by analyzing
 331 only those STL triangles whose bounding pan and tilt angles surround pan_0
 332 and $tilt_0$. Compared to the spin image approach, the complexity of this object
 333 recognition approach is thus not proportional to the number of search objects.

334 It must be emphasized that this complexity reduction is possible because it
 335 is fairly simple to calculate the bounding angles of a STL triangle and the
 336 intersection of a line with a STL triangle. If the project 3D CAD model was
 337 not expressed using a polygon tessellation-based format, but using a native
 338 CAD format — where each CAD object is represented as the intersection of

339 primitive forms, these calculations would become much more complex.

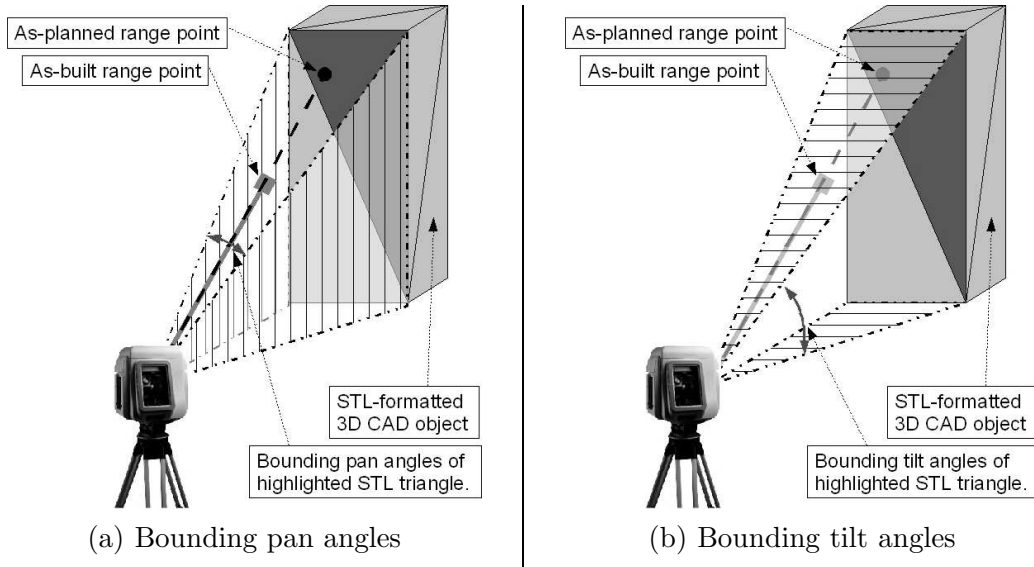


Figure 1. Illustration of the selection of STL triangles based on their bounding pan and tilt angles for identifying the closest STL triangle intersected by a given “ray”.

340 4.3 The Range Point Matching And Object Recognition Metrics

341 Once the as-planned range point cloud has been calculated, it is possible to sort
 342 the as-planned range points by their object “ID/name” feature (the object
 343 from which each of them was obtained). This results in an as-planned range
 344 point cloud for each object constituting the project 3D model (note that each
 345 object for which no as-planned range point was obtained is simply assigned
 346 an empty point cloud). Then, for each object as-planned range point cloud,
 347 each as-planned point can be directly matched to its corresponding as-built
 348 point. This requires a *range point matching metric*. After matching each point
 349 of the object as-planned range point cloud, the recognition of the object can
 350 finally be inferred. This requires a second metric, the *object recognition metric*
 351 (or *object retrieval metric*).

352 4.3.1 Range Point Matching Metric

353 Each as-planned range point corresponds to exactly one as-built range point,
 354 and these two points have the same pan and tilt angles. Their matching can
 355 thus only be estimated based on the only remaining common feature, the
 356 range coordinate (although if additional common features exist, they should
 357 certainly be used). A range point matching metric can thus simply consider
 358 the difference in their ranges and compare it to a given threshold. For instance,
 359 an as-planned range point can be considered positively matched to its corre-

360 sponding as-built point if the absolute difference in their ranges, $\Delta Range$, is
361 lower than the distance threshold, $\Delta Range_{min}$.

362 In Section 7, the authors discuss a method to automatically define an adequate
363 $\Delta Range_{min}$ threshold that takes into account context-specific factors. In the
364 experiments presented in Section 5, a manually *a priori* estimated threshold
365 is however used.

366 4.3.2 Object Recognition Metric

367 For each project object, once the matching of all as-planned range points with
368 their corresponding as-built range points has been assessed, the recognition
369 of the object can be inferred. For this, a straight-forward and commonly used
370 object recognition/retrieval metric is used: the calculation of the object as-
371 planned point cloud *retrieval rate*, $R_{\%}$, which is the ratio of the number of
372 retrieved as-planned range points to the total number of as-planned range
373 points. $R_{\%}$ can be compared to a threshold $R_{\%min}$ to infer the object recog-
374 nition/retrieval. It is not however obvious what value $R_{\%min}$ should take. In
375 fact, whatever the value of $R_{\%min}$, this metric, as is, will not be robust in the
376 following two cases:

377 **Object as-planned point cloud containing only a few points.** For in-
378 stance, if an object as-planned point cloud contains two points and if one
379 point is recognized, then 50% of the as-planned point cloud is retrieved.
380 Clearly, such a situation — that can occur when the object is far or very
381 occluded, or when the range point cloud density is low — should not lead
382 to the recognition of the object, despite the high point cloud retrieval rate.
383 **Object occluded by non-CAD objects.** This may result in objects hav-
384 ing unreasonably low retrieval rates although many points are actually re-
385 trieved. For instance, in the case where 5% of an as-planned point cloud
386 containing 2000 points is retrieved, the retrieval rate is very low, but there
387 are still 100 retrieved points and it could be argued that the object should
388 be considered retrieved.

389 The first situation can be handled by adding to the retrieval metric the condi-
390 tion that an object can only be considered for retrieval if its as-planned range
391 point cloud contains a minimum number of points, defined by a threshold
392 P_{nmin} . The second situation can be handled by adding to the retrieval metric
393 the condition that, if the number of recognized as-planned points is higher
394 than a given threshold R_{nmin} , this is sufficient to consider the object retrieved
395 (no need to calculate the as-planned cloud retrieval rate).

396 Like for the point matching metric, the authors discuss in Section 7 methods
397 to automatically estimate adequate P_{nmin} , R_{nmin} and $R_{\%min}$ threshold values
398 by taking into consideration the context-specific factors such as: the scan point

399 density and distance between the scanner and each search object. However, in
 400 the experiments presented in Section 5 these thresholds are manually *a priori*
 401 estimated.

402 This final CAD object as-planned point cloud retrieval metric is summarized
 403 in Figure 2. The pseudo-code of the overall proposed approach is presented in
 404 Figure 3.

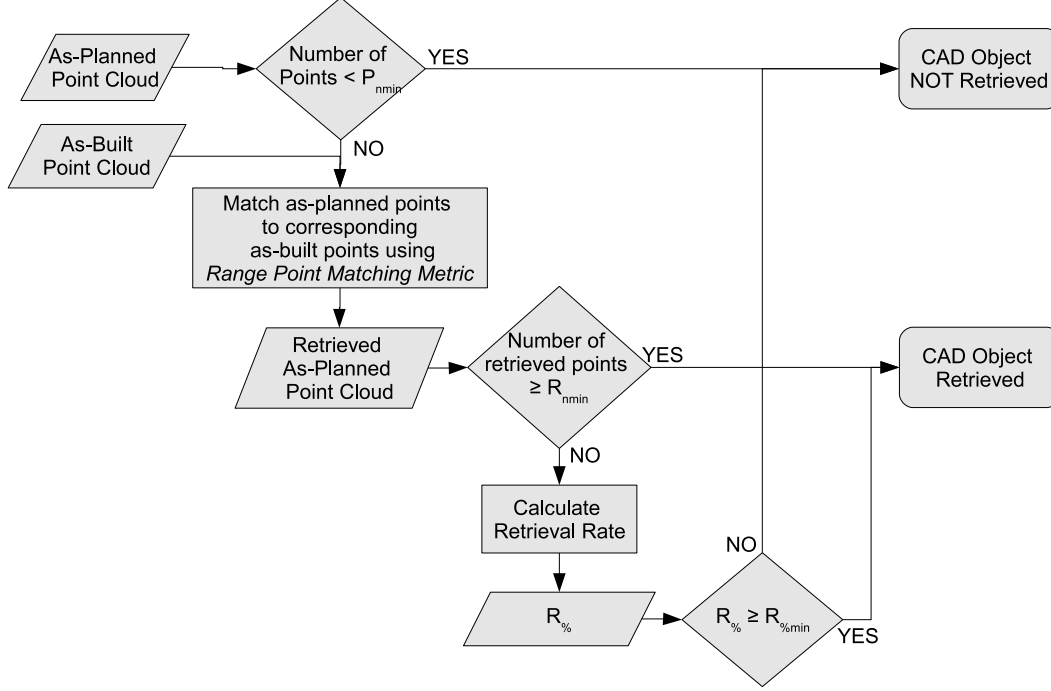


Figure 2. Object recognition/retrieval metric.

405 5 Experimental Results

406 In order to test the proposed approach, two indoor experiments have been con-
 407 ducted using a simple structure made of four columns and one board simulat-
 408 ing a column-slab structure, a TrimbleTM GX3D laser scanner — the charac-
 409 teristics of which are presented in Table 1, and the 3D CAD engine BentleyTM
 410 MicrostationTM. The first experiment aims at validating the approach. The
 411 second experiment aims at demonstrating how this approach could be success-
 412 fully used for automated construction progress assessment.

413 It must be noted that, in these experiments, referencing is not performed using
 414 global positioning sensors but is simply performed manually, and referencing
 415 uncertainties are not considered. Also, as mentioned earlier, the thresholds
 416 used in the two metrics are manually *a priori* estimated.

```

Build As-Planned Point Cloud:
for each as-built point  $P(pan; tilt; range)$  do
  CREATE as-planned point  $P'(pan' = pan; tilt' = tilt; range' = +\infty; ID' = NaN)$ 
  for each STL-formatted object do
    for each STL triangle do
      if  $pan' \geq pan_{STLmin}$  &  $pan' \leq pan_{STLmax}$  &  $tilt' \geq tilt_{STLmin}$  &  $tilt' \leq tilt_{STLmax}$  then
        if  $ray(pan', tilt')$  intersects STL triangle & intersection point is closer
          UPDATE  $range'$ ;
          UPDATE  $ID'$ ;
        end
      end
    end
  end
end
SORT as-planned point cloud by  $ID'$ ;

For each CAD object, retrieve each individual point, deduce
retrieval metric values, and finally infer its retrieval:
for each CAD object do
  COMPUTE number of as-planned points,  $P_n$ ;
  if  $P_n < P_{nmin}$  then
    CAD object is NOT RETRIEVED;
  else
    for each as-planned cloud point do
      COMPUTE Range Difference,  $\Delta Range$ ;
      if  $\Delta Range \leq \Delta Range_{max}$  then
        As-planned point is retrieved ;
      else
        As-planned point is not retrieved ;
      end
    end
    COMPUTE Number of retrieved as-planned points,  $R_n$ ;
    if  $R_n \geq R_{nmin}$  then
      CAD object is RETRIEVED ;
    else
      COMPUTE Retrieval rate,  $R_{\%}$ ;
      if  $R_{\%} \geq R_{\%min}$  then
        CAD object is RETRIEVED ;
      else
        CAD object is RETRIEVED ;
      end
    end
  end
end

```

Figure 3. Algorithm for automated recognition/retrieval of STL-formatted project 3D CAD model objects in range point clouds.

417 5.1 Experiment 1: Approach Validation

418 5.1.1 Setup

419 In this first experiment, a 3D CAD model of the column-slab structure is ini-
 420 tially developed using the 3D CAD engine and converted into STL format.

Table 1
Specifications of the Trimble GX3D Scanner

Model		GX3D
Laser type		Pulsed; 532nm; green
Distance	Range	2m to 200m
	Accuracy	1.5mm at 50m; 7mm at 100m
Angle	Range	Pan: 360deg Tilt: 60deg
	Accuracy	Pan: 60 μ rad Tilt: 70 μ rad

421 This model is composed of five CAD objects called: *column_1*, *column_2*, *col-*
422 *umn_3*, *column_4*, and *slab* (Figure 4). Then, the structure is manually built
423 with as much precision as possible with respect to the 3D CAD model. Next,
424 the entire scene is scanned with the laser scanner and the STL-formatted
425 project 3D CAD model is manually referenced in the laser scanner's coordi-
426 nate frame. Finally, the developed algorithm is run to automatically retrieve
427 the STL-formatted 3D objects in the range data. Figure 5 shows the labora-
428 tory experimental setup with the column-slab structure and the laser scanner.
429 Figure 6 displays the scene scan containing 206,360 points, the size of each
430 being proportional to its associated reflectivity. The following algorithm input
431 parameters are used:

432 **$\Delta Range_{min}$** . An as-planned cloud point is considered retrieved if the dif-
433 ference between its range and the range of the corresponding as-built point
434 is less than 30 mm ($\Delta Range_{min}$). Construction generally aims at achieving
435 dimensional accuracy within 10-20mm at most. Therefore, the authors con-
436 sider that this threshold value is sufficiently high so that objects will not be
437 missed due to some low construction dimensional quality, without creating
438 false positive matches.

439 **P_{nmin}** . The retrieval of a CAD object is performed only if its as-planned point
440 cloud contains more than 100 points. This value is set somewhat arbitrarily
441 and, as will be seen in the results, does not have an effect in this experiment.

442 **R_{nmin}** . A CAD object is considered detected if at least 500 points of its as-
443 planned point cloud are retrieved. Here also, this value is defined somewhat
444 arbitrarily and its value does not have any specific impact in the context of
445 this experiment.

446 **$R\%_{min}$** . If less than 500 points (R_{nmin}) of a CAD object as-planned point
447 cloud are retrieved, the object is considered retrieved only if its as-planned
448 range point cloud retrieval rate is at least 50%. As discussed earlier, it is not
449 obvious at this point in this research what is an acceptable $R\%_{min}$ value. As
450 a result, in the absence of any *a priori* knowledge for setting this threshold,
451 the authors decided to choose this midpoint value.

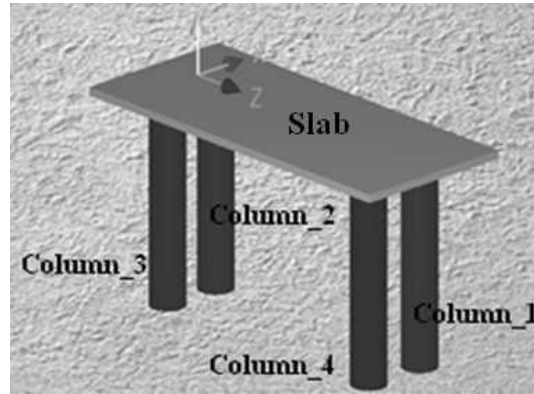


Figure 4. 3D CAD model of the column-slab structure.



Figure 5. Indoor setup with the scanned structure and the laser scanner.

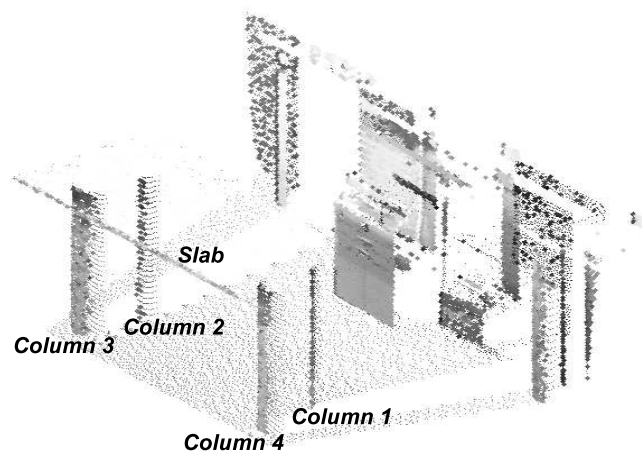


Figure 6. Experiment 1 range point cloud. The size of each point is proportional to its scanning reflectivity.

452 5.1.2 Results

453 The retrieval results are presented in Figure 7 and Table 2. Figure 7 displays
 454 the as-built, as-planned, and retrieved as-planned data. In this figure, only
 455 1% of the total number of points of each cloud is actually displayed in order
 456 to increase picture clarity. Also, in the retrieved as-planned point cloud, re-
 457 trieved as-planned points are displayed with circles and non-retrieved ones are
 458 displayed with asterisks.

459 Table 2 shows that all CAD objects from the 3D CAD model are retrieved. The
 460 retrieval rates of all CAD objects are high (at least 74%), including *column_1*
 461 and *column_2* despite the fact that, as can be seen in Figure 6, about 60%
 462 of their normally visible surfaces are occluded by *column_4* and *column_3*
 463 respectively. This demonstrates the robustness of this method with respect to
 464 occlusions due to other CAD objects.

465 It is also interesting to note that the slab is detected with a high but slightly
 466 lower retrieval rate (74%) than the other objects. A reason for this can be found
 467 in Figure 6. Remember that in this figure the size of each point is proportional
 468 to its associated reflectivity. Reflectivity can be seen as an estimator of range
 469 acquisition uncertainty, and it can be noticed that most points obtained from
 470 the slab, especially from its top surface, have a very low reflectivity. The
 471 manually set $\Delta Range_{min}$ threshold might thus have been too low to retrieve
 472 these specific points. Another reason could be error in vertical referencing.
 473 Indeed, in this example, a little error in the vertical referencing would shift the
 474 as-built slab cloud compared to the as-planned one, which would considerably
 475 alter the object retrieval results. The effect of referencing uncertainty is further
 476 discussed in Section 6.

Table 2

Retrieval results of Experiment 1.

Calculated Values	CAD Element				
	<i>column_1</i>	<i>Column_2</i>	<i>Column_3</i>	<i>Column_4</i>	<i>Slab</i>
Number of As-Planned Points	5,079	4,678	17,490	17,880	4,712
Number of Retrieved As-Planned Points	4,423	4,411	16,403	16,120	3,479
Retrieval Rate of As-Planned Points	87%	94%	94%	90%	74%
Detected	YES	YES	YES	YES	YES

477 Although these experimental results are very positive, it is acknowledged that
 478 they were obtained in a somewhat ideal indoor setup. In fact, in this ex-
 479 periment, all CAD objects are retrieved without considering retrieval rates
 480 (even *column_1* and *column_2*) as the total number of retrieved points are
 481 always higher than R_{nmin} . In field situations, it is likely that the number of
 482 retrieved points, the retrieval rates and the number of as-planned points would
 483 not always be so high, in which case the values of the corresponding thresh-

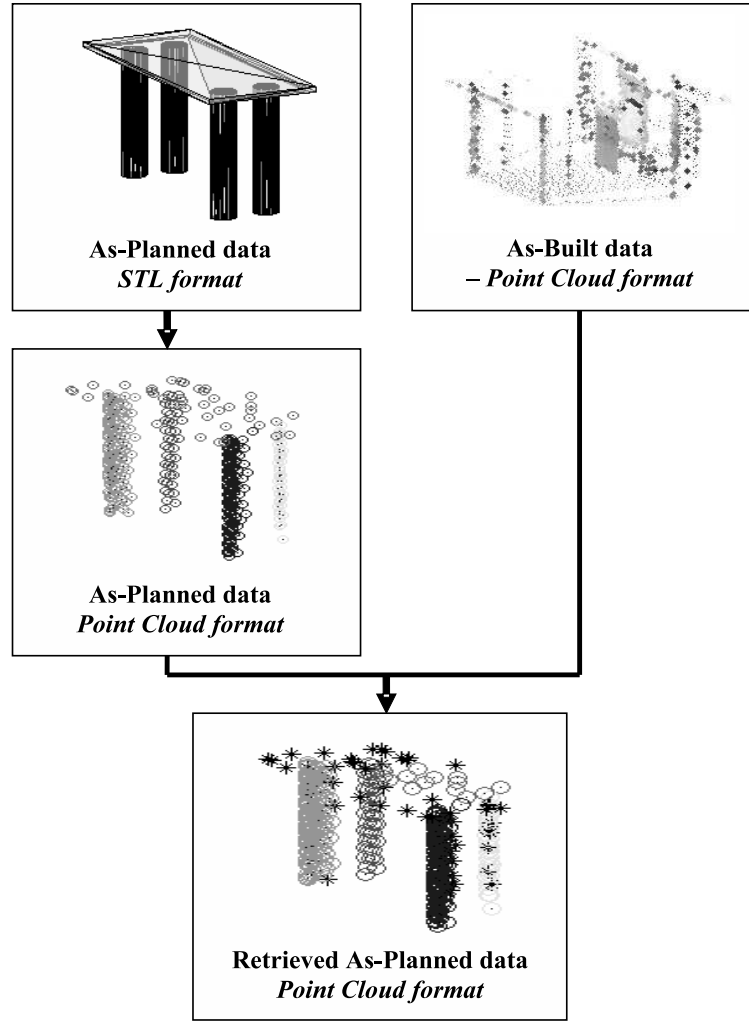


Figure 7. As-built and as-planned data at different stages of the retrieval process in Experiment 1 (only 1% of the total number of points of each cloud is displayed to increase clarity).

olds ($\Delta Range_{min}$, P_{nmin} , R_{nmin} and $R_{\%min}$) would have a higher impact on the retrieval results. More robust methods to automatically estimate these thresholds are thus suggested in Section 7.

5.2 Experiment 2: Application to Construction Progress Assessment

5.2.1 Setup

The goal of this second experiment is to demonstrate how this new approach could be applied to automated construction progress assessment. In this experiment, the same setup is used. The difference is that instead of a project 3D CAD model, a project 4D CAD model is used. It is built using the project 3D CAD model displayed in Figure 4 and the simple construction schedule,

for which the bar chart is shown in Figure 8(a). The resulting as-planned project 4D CAD model is displayed in Figure 9(a). Then, the same scene as in Experiment 1 is scanned (Figure 6) and is assumed to occur on day 4 of the construction. The goal of the experiment is to retrieve all project 3D objects in the scan, and identify whether construction is on schedule, early, or late. The following input parameters are used:

Schedule Uncertainty. A one-day uncertainty in schedule is used so that work completed earlier or later by one day can be identified. This implies that the scanned data is compared with three consecutive project 3D CAD models extracted from the project 4D CAD model and centered on the day when the scan is conducted (here day 4).

$\Delta Range_{min}$. Same as in Experiment 1 (30mm).

P_{nmin} . Same as in Experiment 1 (100 points).

R_{nmin} . Same as in Experiment 1 (500 points).

$R\%_{min}$. Same as in Experiment 1 (50%).

5.2.2 Results

Table 3 summarizes the results obtained in this experiment. It shows that all 3D objects in day 5 project 3D model are retrieved in the scanned data. The retrieval of each object is made with a minimum of 4,500 retrieved as-planned points per object and very high retrieval rates. Since the scan is assumed to take place on day 4, it can be concluded that construction is one day ahead of schedule. The bar chart of a possible resulting as-built schedule is displayed in Figure 8(b) and the corresponding as-built 4D CAD model is presented in Figure 9(b).

Certainly, the metric used here to identify early, on time or late construction is very basic. However, these results demonstrate that this approach has great potential for supporting automated project work progress tracking.

ID	Task Name	Duration	31 Dec 2006				
			1	2	3	4	5
1	Column_1	1d	■				
2	Column_2	1d		■			
3	Column_3	1d			■		
4	Column_4	1d				■	
5	Slab	1d					■

(a) As-planned Schedule

ID	Task Name	Duration	31 Dec 2006				
			1	2	3	4	5
1	Column_1	1d		■			
2	Column_2	1d			■		
3	Column_3	1d				■	
4	Column_4	1d					■
5	Slab	1d					■

(b) As-built Schedule

Figure 8. As-planned and as-built schedules of the construction of the column-slab structure

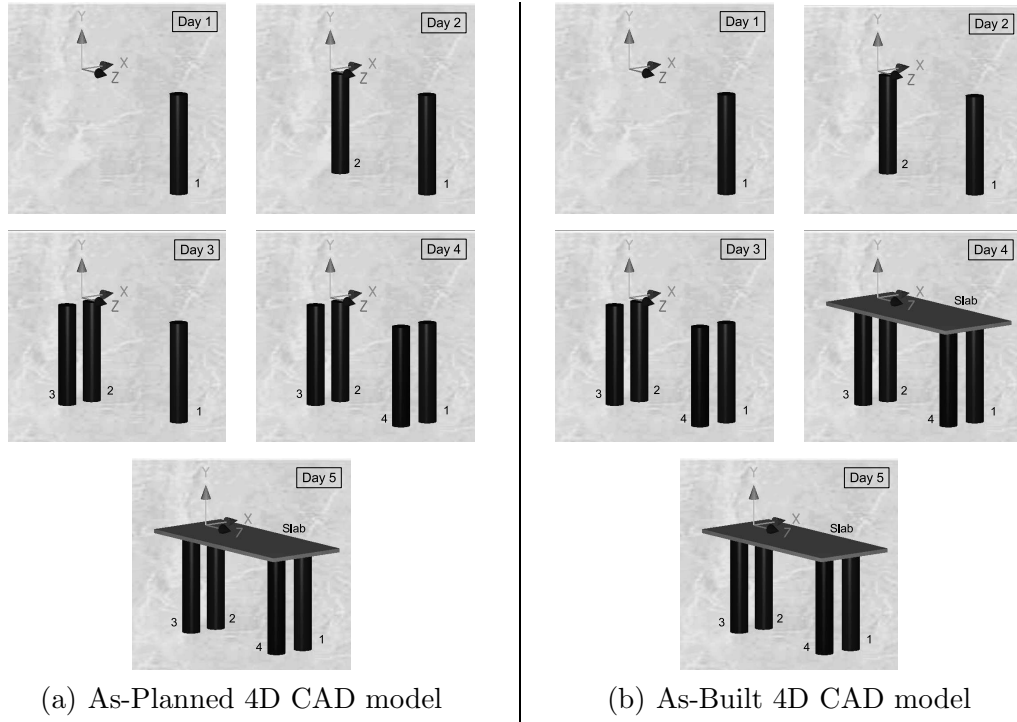


Figure 9. As-planned and as-built 4D CAD models of the construction of the column-slab structure

Table 3

Retrieval results in Experiment 2

Day	Calculated Values	CAD Element				
		column_1	Column_2	Column_3	Column_4	Slab
3	Number of As-Planned Points	15,042	4,678	17,490	0	0
	Number of Retrieved As-Planned Points	4,684	4,411	16,403	0	0
	Retrieval Rate of As-Planned Points	31%	94%	94%	0%	0%
	Detected	YES	YES	YES	NO	NO
4	Number of As-Planned Points	5,079	4,678	17,490	17,880	0
	Number of Retrieved As-Planned Points	4,423	4,411	16,403	16,120	0
	Retrieval Rate of As-Planned Points	87%	94%	94%	90%	0%
	Detected	YES	YES	YES	YES	NO
5	Number of As-Planned Points	5,079	4,678	17,490	17,880	4,712
	Number of Retrieved As-Planned Points	4,423	4,411	16,403	16,120	3,479
	Retrieval Rate of As-Planned Points	87%	94%	94%	90%	74%
	Detected	YES	YES	YES	YES	YES

6 Impact of measurements uncertainties

The previous experiments were conducted with somewhat ideal conditions and all measured values were considered exact. In construction site applications, measurement uncertainty could be non negligible and should therefore be es-

525 timated and taken into account in the object retrieval process. In the investi-
526 gated problem, measurement uncertainties include: *referencing uncertainties*
527 and *laser measurement uncertainties*.

528 6.1 Referencing uncertainties

529 Referencing uncertainties refer to uncertainties in the 3D CAD model geo-
530 referencing or/and in the range point cloud geo-referencing. These can be
531 translated into a single set of referencing uncertainties which is the difference
532 between the real and virtual geo-positions of the laser scanner. This referenc-
533 ing uncertainty includes uncertainties in location (*northing, easting, altitude*)
534 and in orientation (*heading, pitch, roll*). *Northing, easting, altitude, heading,*
535 *pitch* and *roll* can be obtained using different global positioning technolo-
536 gies. However, the accuracy that these technologies can currently achieve is
537 limited to several centimeters in location and half a degree in orientation at
538 best. These uncertainties are significant enough that their impact on object
539 recognition systems that use these technologies can be non-negligible.

540 A method is suggested here for the automated correction of referencing error.
541 This correction can be made prior to performing the actual point retrieval
542 process. For each of the six 3D model referencing parameters (*northing, east-*
543 *ing, altitude, heading, pitch* and *roll*), uncertainty is modeled with a discrete
544 distribution with three values centered on the measured one. Then, for each
545 combination of six discrete values (one discrete value for each of the six pose
546 parameters), the retrieval of a fixed number of random range points, $n_{rpoints}$
547 (for instance $n_{rpoints} = 600points$) is performed using the approach described
548 in this paper. The likelihood of each combination being the best referencing is
549 calculated using a mean square error estimator based on the range differences
550 between the $n_{rpoints}$ as-built points and their corresponding as-planned points.
551 The best referencing estimation is the one with the lowest mean square error.
552 If a better referencing is identified for a set of six values with at least one of
553 them different from its corresponding measured one, the measured values are
554 correspondingly updated and this process is reiterated. This iteration occurs
555 until the best pose is the one with the six parameters set to their measured
556 values.

557 Although each pose improvement increment requires the analysis of 3^6 com-
558 binations of discrete pose values, note that the complexity of this method is
559 fixed with respect to the number of as-built range points, as only a subset of
560 a fixed number of points is used. Also, it is acknowledged that this method
561 requires estimating the parameters necessary for the description of the dif-
562 ferent discrete distributions (distribution type, space between values in each
563 distribution, n_{unc}). Previous research using likelihood estimators suggest that

a value of $n_{rpoints} = 100 \cdot n_{param}$, where n_{param} is the number of uncertainty parameters (here six), is statistically sufficient. Then, the type of discrete distribution to use is not obvious. By default, it is thus suggested to consider equal probabilities for each discrete value (uniform discrete distribution). Finally, the space between values in each distribution could be set as one time or half the measurement uncertainty.

At this time, this correction approach has only been tested a couple of times, using manually defined discrete uniform distributions. While the results seemed fairly good, a comprehensive set of experiments would be required to confirm the efficiency and robustness of this approach for automated pose correction. Additionally, the adequacy of basing the mean square error estimator on range differences can be discussed. Indeed, range difference may provide different results than orthogonal projection distance which is more commonly used because more intuitive.

6.2 Laser measurement uncertainties

Laser measurement uncertainties relate to the uncertainties in the measurement of each individual point. They include uncertainties in pan, tilt and range values.

Pan and tilt uncertainties result from imperfections in the laser scanner embedded pan&tilt unit. While pan and tilt uncertainties are independent from the scanned surface, it must be noted that they are also generally considered value independent. Pan and tilt uncertainties are provided by laser scanner providers. In the case of the scanner used in this research, pan and tilt uncertainties are respectively $60\mu rad$ and $70\mu rad$ ($0^{\circ}0'12''$ and $0^{\circ}0'14''$). These respectively translate into $0.6mm$ and $0.7mm$ accuracy at $10m$, or $6mm$ and $7mm$ accuracy at $100m$. A common approach to take such uncertainties into account when determining a point range is to analyze the ranges of all the points neighboring the studied one. Such an approach is however inappropriate here since the pan and tilt angle uncertainties are much lower than the maximum pan and tilt point densities that the scanner can achieve. Another more computationally complex method is the calculation for each point of several “intermediate” range values obtained with different combinations of pan and tilt angles adjusted with uncertainty. All the “intermediate” ranges could then be analyzed to infer the most probable point range. This method is similar to the one proposed above for referencing correction.

Range uncertainty is related to several factors including: the scanning angle to the scanned surface, the material of the scanned surface, environmental conditions, etc. Range measurement uncertainty is generally provided by laser

scanner providers for specified material reflectivity and with scanning directions perpendicular to the scanned surface. The laser scanner used in the experiments above presents the following range “best” uncertainties: $1.5mm$ at $50m$ and $7mm$ at $50m$ for 100% reflective targets. A possible method to take range measurement uncertainty into account when matching two as-built and as-planned points is presented in Section 7.2 when discussing the automated estimation of the threshold parameter $\Delta Range_{nmin}$.

Overall, it must be emphasized that these laser measurement uncertainties remain negligible when compared with current geo-referencing uncertainties.

7 Thresholds Parameters Estimation

The proposed object recognition approach uses two metrics that require some input threshold parameters: $\Delta Range_{min}$, P_{nmin} , R_{nmin} and $R_{\%min}$. In the experiments presented in this paper, these thresholds were manually *a priori* estimated. But for a complete automated approach, these would have to be automatically estimated, especially since their values should be adjusted to different scanning and scene condition factors.

7.1 P_{nmin} , R_{nmin} and $R_{\%min}$

In the *object recognition metric*, P_{nmin} , R_{nmin} and $R_{\%min}$ could be estimated by taking into consideration the following factors:

Scan point density. The scan point density is the pan and tilt difference between two neighboring points. If a scene is scanned twice with two different point densities, one twice denser than the other, the as-built and resulting as-planned point clouds of each scanned object will contain twice more points in the denser scan. It is therefore possible that for a given manually *a priori* estimated P_{nmin} value, an object is considered for search with the denser scan and not with the less dense one. Similarly, it is possible that for a given manually *a priori* estimated R_{nmin} , the retrieval rate of an object will have to be calculated with the less dense scan, but not with the denser one. Since scan point density should not have any effect on the retrieval metrics, P_{nmin} and R_{nmin} must be adjusted to it: $P_{nmin} = f_1(d_{scan})$ and $R_{nmin} = f_2(d_{scan})$, where the functions $f_1()$ and $f_2()$ could be *a priori* experimentally estimated. Note, that $R_{\%min}$ is not impacted by the scan point density as it is expressed as a percentage of points that is invariant with this factor.

Scanner-object (or scanner-STL triangle) distance. The same argument

can be made with two exactly similar objects that are at different distances from the scanner, one twice further than the other. P_{nmin} and R_{nmin} should thus be automatically adjusted for each object, and consequently for each STL triangle, by taking the as-planned scanner-STL triangle distance into account. The as-planned distance between the scanner and a STL triangle, $Range_{STL}$, can be estimated as the mean of the distance between the scanner and the three STL triangle vertices. As a result, P_{nmin} and R_{nmin} could be further customized for each STL triangle such that: $P_{nmin}^{STL} = f_1^{STL}(d_{scan}, Range_{STL})$ and $P_{nmin}^{STL} = f_2^{STL}(d_{scan}, Range_{STL})$, where the functions $f_1^{STL}()$ and $f_2^{STL}()$ could be *a priori* experimentally estimated. Note again that $R_{\%min}$ is not impacted by the scanner-STL triangle distance as it is expressed as a percentage of points that is invariant with this factor.

While methods for automating the estimation of P_{nmin} and R_{nmin} are presented here, no method is suggested for $R_{\%min}$. For $R_{\%min}$, the authors suggest, with lack of experience to use the midpoint value of 50%.

7.2 $\Delta Range_{nmin}$

In the *point matching metric*, $\Delta Range_{min}$ could be estimated by taking into consideration the following factors:

Range. As presented earlier, range measurement uncertainty depends on many factors. It is nonetheless generally provided by laser scanner providers for specified material reflectivity and with scanning directions perpendicular to the scanned surface. In Section 6.2, it can be seen in the specifications of the scanner used in this research that range uncertainty increases with range (this is true for any scanner). Therefore, the threshold parameter $\Delta Range_{min}$ should be customized for each scanned point, p : $\Delta Range_{min}^p = f_3^p(Range_p)$, where $Range_p$ is the measured range of point p , and $f_3^p()$ could be estimated *a priori* through multiple experiments.

Reflection angle. Uncertainty in range acquisition increases with the reflection angle between the point scanning direction and the scanned surface normal vector. The impact of the reflection angle on range uncertainty is illustrated in Figure 10. The as-planned reflection angle of each as-planned range point could be estimated when calculating the as-planned point. This estimation could then be used to further customize the $\Delta Range_{min}^p$ threshold: $\Delta Range_{min}^p = f_3^p(Range_p, RefAngle_{STL})$, where $RefAngle_{STL}$ is the point p as-planned reflection angle, and $f_3^p()$ could be *a priori* experimentally estimated.

Surface reflectivity. Finally, acquired range uncertainty decreases with surface reflectivity. If an estimated object surface reflectivity could be obtained from the material applied to the objects in the original project 3D CAD

676 model, then each STL triangle could be assigned an estimated reflectivity
 677 and the function $f_3^p()$ and consequently the threshold $\Delta Range_{min}^p$ could be
 678 further customized.

679 Overall, while methods for automatically estimating the different input pa-
 680 rameters used in the proposed object retrieval approach are presented here,
 681 these still require the predetermination of some functions $f_1^{STL}()$, $f_2^{STL}()$ and
 682 $f_3^p()$ through a comprehensive set of experiments. These experiments have not
 683 been conducted yet and would require a complex test bench. The need for such
 684 experiments has been expressed in previous work and the National Institute
 685 for Standards and Technology (NIST) has been working on the construction
 686 of such a facility for comprehensive LADAR performance evaluation [16].

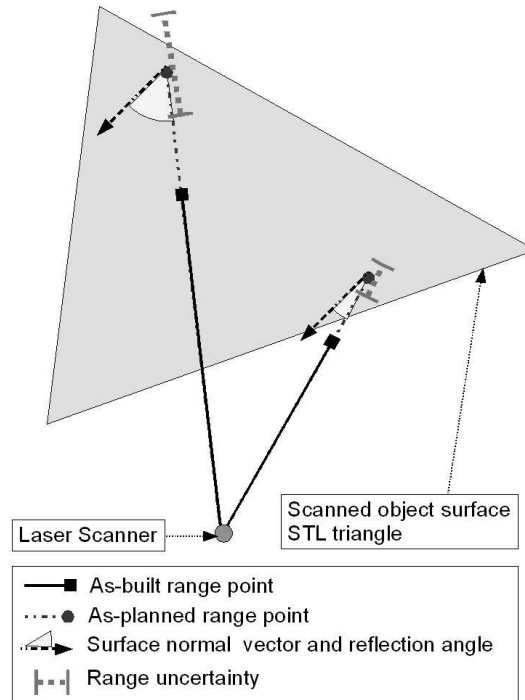


Figure 10. Impact of the reflection angle on the acquired range uncertainty.

687 8 Conclusion and Future Work

688 The cost of 3D range scanning is rapidly declining due to recent developments,
 689 and use of 3D images is increasing accordingly. In this paper, a new approach
 690 for automatically retrieving 3D CAD objects in 3D range point clouds is pre-
 691 sented. This approach takes advantage of 3D/4D CAD models and (geo-)
 692 referencing technologies. Experimental results first demonstrate that this com-
 693 pletely automated approach is quite robust, including in the case of occlusions
 694 due to other CAD elements. The second experiment further illustrates these

695 strengths and demonstrates how it could robustly support applications such
696 as automated construction progress tracking. Future work will focus on con-
697 firming these results with full-scale structures. The impact of uncertainties in
698 (geo-) referencing values and in point measurement values will be further inves-
699 tigated, and methods for automating the estimation of the required threshold
700 parameters will also be further tested.

701 Finally, the authors would like to re-emphasize the fact that this new approach
702 has applications not only in automated construction work progress tracking,
703 but also in construction quality control, in 3D image database information
704 retrieval, and very likely in many other areas.

705 9 Acknowledgements

706 This project is partially funded by a grant from the National Science Foun-
707 dation grant #0409326 and the Canada Research Chair in Construction &
708 Management of Sustainable Infrastructure.

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